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Spatial Effects of Financial Resource Allocation Efficiency on Green Total Factor Productivity

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Abstract: *Accelerating the realization of green development has gradually become the mainstream trend of economic and social transformation, and efficient financial resource allocation can provide financing support and risk management for green economic transformation. The study analyzes the impact of financial resource allocation efficiency on green total factor productivity by constructing a dynamic spatial Durbin model with panel data of 30 regions in China from 2011 to 2022. The results show that financial resource allocation efficiency can promote the green total factor productivity of local and neighboring regions in the short term, and in the long term, it has a more significant role in promoting local green total factor productivity. Efforts should be made to promote the rational allocation of financial resources, reduce the financing threshold for enterprises and green projects; promote the deep integration of financial science and technology with the green industry; and strengthen financial supervision, as well as the evaluation and testing of green financial projects.*

Keywords: *Financial Resource Allocation Efficiency; Green Total Factor Productivity; Dynamic Spatial Durbin Modeling*

1. Introduction

In the face of increasingly severe environmental challenges and extreme natural climate issues, sustainable development has become a crucial global agenda. The transition to a green economy is now a consensus and action plan within the international community. Governments and international organizations worldwide are formulating and implementing policies and measures to drive economic development towards a green and low-carbon trajectory. Finance, as the core industry of the modern economy, plays a pivotal role in allocating more financial resources to the key areas and weak links of economic and social development, which is essential for deepening supply-side structural reforms and achieving high-quality economic development during China's economic transition. The rational allocation of financial resources is crucial for promoting economic growth, fostering innovation, and enhancing resource utilization efficiency. Efficient financial resource allocation can provide the necessary financing support and risk management, thus offering essential funds and resources for the green economy transition.

Given China's unique geographical distribution, there is significant regional heterogeneity in the distribution of financial resources and the degree of green development across different areas. Studying the spatial effects of financial resource allocation efficiency on green total factor productivity helps to identify regional disparities, expand existing theories of resource allocation, and contribute to the theoretical framework of green economic development.

2. Literature Review

On measuring green total factor productivity. Green Total Factor Productivity (*GTFP*) refers to a metric that encompasses both desired and undesired outputs, considering economic and environmental benefits to seek a coordinated development between the economy and ecology. (Chung et al., 1997) first proposed the inclusion of "bad" outputs in GTFP measurement [1]. Using Data Envelopment Analysis (DEA), they employed the Malmquist-Luenberger (ML) index to estimate total factor productivity inclusive of undesirable outputs, thereby introducing the concept of GTFP. However, the use of DEA for estimation introduces radial and angular biases, and the ML index does not satisfy transitivity and additivity. To address these issues, (Tone, 2001) improved the DEA model by proposing the Slack-Based Measure (SBM) model [2], while (Oh, 2010) developed the Global Malmquist-Luenberger (GML) index

[3]. The GML index based on the SBM directional distance function effectively addresses radial and angular issues.

Regarding the measurement of financial resource allocation efficiency, (Yeh et al., 2010) analyze and compare the operational efficiency of 14 securities firms in Taiwan's financial holding system and 12 securities firms in the non-financial holding system by using data envelopment analysis (DEA) and Tobit regression model with corporate governance variables [4]. (Rahmani et al., 2014) conducted a non-parametric frontier analysis of the efficiency and performance of Iranian insurance companies [5]. (Li, 2014) employed principal component analysis to assess the efficiency of rural financial resource allocation across various regions of China [6]. (Dai et al., 2016) used the DEA model to measure China's financial resource allocation efficiency from the three aspects of economic efficiency, social efficiency and eco-efficiency, and evaluated the efficiency changes by using the Malmquist index [7]. (Liu, 2019) utilized Wurgler's investment elasticity coefficient model to measure the efficiency of financial resource allocation in Harbin city and its county-level areas [8]. (Guo et al., 2021) employed the entropy power method to measure the financial resource allocation across 30 provinces in China from 2002 to 2019 [9]. (Zhang et al., 2022) applied the DEA-Malmquist method to assess the efficiency of financial resource allocation in 12 provinces and municipalities in western China. They investigated the influencing factors and their relationship with economic growth objectives [10]. (Guo et al., 2024) measured the financial efficiency of the Beijing-Tianjin-Hebei region using the information entropy-based SBM model. They examined the impact of financial resource allocation on economic growth and development, focusing on aspects such as financial development, industrial structure upgrading, innovation, and infrastructure construction [11].

3. Variables and Research Methodology

3.1 Variable Description

Dependent Variable: This study employs the GML index based on the SBM directional distance function to measure GTFP, assuming constant returns to scale (CRS).

First, each province is considered a decision-making unit (DMU_k). Assume each DMU_k has N types of input factors $= (x_1, \cdots, x_N) \in R_N^+$, producing M types of desired outputs $y = (y_1, \cdots, y_M) \in R_M^+$, and I types of undesired output$b = (b_1, \cdots, b_N) \in R_I^+$. The input-output for each DMU_k at period t is (x^{kt}, y^{kt}, b^{kt}), forming the global production possibility set as in Equation (1).

$$P^t(x^t) = \{(y^t, b^t): \sum_{k=1}^{K} Z_k^t y_{km}^t \geq y_{km}^t,$$

$$\forall m; \textstyle\sum_{k=1}^{K} Z_{ki}^t b_{ki}^t = b_{ki}^t, \sum_{k=1}^{K} Z_k^t y_{kn}^t \leq x_{kn}^t, \forall n; Z_k^t \geq 0, k = 1, \cdots, \mathrm{K}\} \tag{1}$$

where Z_k^t represents the weight for each cross-section, indicating constant returns to scale (CRS) when $Z_k^t \geq 0$.

The SBM directional distance function is given by Equation (2):

$$\vec{S}_V^G\left(x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b\right) = \max_{s^x, s^y, s^b} \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x} + \frac{1}{M+I}\left(\sum_{m=1}^{M}\frac{s_m^y}{g_m^y} + \sum_{i=1}^{I}\frac{s_i^b}{g_i^b}\right)}{2} \tag{2}$$

$$s.t. \sum_{k=1}^{K} Z_k^t x_{kn}^t + s_n^x = x_{k'n}^t, \forall\, n; \sum_{k=1}^{K} Z_k^t y_{km}^t - s_m^y = y_{k'm}^t, \forall\, m; \sum_{k=1}^{K} Z_k^t b_{ki}^t + s_i^b = b_{k'i}^t, \forall\, i;$$

$$\sum_{k=1}^{K} Z_k^t = 1\,, Z_k^t \geq 0, \forall\, k; s_n^x \geq 0, \forall\, n; s_m^y \geq 0, \forall\, m; s_i^b \geq 0, \forall\, i$$

where $(x^{t,k'}, y^{t,k'}, b^{t,k'})$ represents the input-output vector for DMU_k, and (g^x, g^y, g^b) represents the directional vectors for reducing inputs, increasing desired outputs, and reducing undesired outputs. The slack variables (s_n^x, s_m^y, s_i^b) represent the amounts of input surplus, desired output shortfall, and excess undesired output, respectively.

The GML index is defined by Equation (3), representing the change from period t to period t+1. GML index greater than 1 indicates growth in GTFP, less than 1 indicates a decline, and equal to 1 indicates

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stability.

$$GML_t^{t+1}=\frac{1+\vec{S}_V^G(x^t,y^t,b^t;g^x,g^y,g^b)}{1+\vec{S}_V^G(x^{t+1},y^{t+1},b^{t+1};g^x,g^y,g^b)}=GEC_t^{t+1}\cdot GTC_t^{t+1} \tag{3}$$

Table 1 shows the construction of green total factor productivity indicators.

Table 1: Construction of green total factor productivity indicators

	Indicator
Inputs	Number of employed persons in urban units
	Fixed capital stock
	Energy consumption (tonnes of standard coal)
Desired Outputs	Actual GDP
Undesired Outputs	CO2 emissions
	Industrial SO2 emissions
	Industrial wastewater emissions
	General industrial solid waste

Independent Variable: Financial resource allocation efficiency (FIN). (Tone, 2002) developed the super-efficiency SBM model to further evaluate the efficiency values of optimal decision-making units.

For DMU(x_0,y_0), the super-efficiency SBM model under CRS is represented by Equation (4):

$$\rho=min\frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{i0}}}{\frac{1}{s}\sum_{k=1}^{s}\frac{\overline{y_k}}{y_{k0}}} \tag{4}$$

$$s.t.\ \overline{x_i}\geq\sum_{j=1,\neq 0}^{n}\lambda_j x_j\,,\forall i;\ \overline{y_k}\leq\sum_{j=1,\neq 0}^{n}\lambda_j y_j\,,\forall k;\ \overline{x_i}\geq x_{i0},0\leq\overline{y_k}\leq y_{k0},\lambda_j\geq 0,\forall i,j,k$$

The efficiency of financial resource allocation is measured using super-efficiency SBM model with indicators constructed as in Table 2.

Table 2: Construction of Financial Resource Allocation Efficiency Indicators

Type of indicator	Name of indicator	Description of indicator
Input	Human Capital Inputs	Number of employees in the financial industry
	Fixed assets input	Investment in Fixed Assets in the Financial Sector
	Loan Capital Input	Balance of Loans from Financial Institutions
	R&D Innovation Input	Investment in R&D Funds
Output	Financial sector output	Value added of financial industry

Control Variable: Industrial Structure (IS): the level of industrial structure is measured by the ratio of the added value of the three major industries to the total regional output value, defined as Equation (5). The Level of Economic Development (ECO) is measured by GDP per capita and treated in logarithmic terms. The Level of Labour Force (LAB) is measured by the resident population at the end of the year and treated in logarithmic terms. The Degree of Government Intervention (GOV) is measured by the proportion of the local government's financial expenditure on environmental protection to the local financial expenditure of the general budget. The Level of Openness to the Outside World (OPEN) is measured by the ratio of total import and export volume to regional gross output. The total import and export volume is calculated based on the domestic destination and source of goods, converted into billion RMB using the annual average of the mid-point exchange rate of the RMB. Urbanisation Level (URB): Measured by the ratio of urban population to resident population at the end of the year.

$$IS=1*\frac{fir}{y}+2*\frac{sec}{y}+3*\frac{thi}{y} \tag{5}$$

where fir, sec, thi and y represents the added value of the primary, secondary, and tertiary industries and the GDP.

Descriptive statistics for all variables are shown in Table 3.

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Table 3: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
GTFP	360	0.879	0.093	0.602	1
FIN	360	0.525	0.24	0.19	1.961
IS	360	2.4	0.123	2.132	2.835
ECO	360	10.868	0.461	9.682	12.156
LAB	360	8.208	0.741	6.342	9.448
GOV	360	0.029	0.009	0.011	0.068
OPEN	360	0.261	0.261	0.007	1.398
URB	360	0.601	0.121	0.35	0.896

3.2 Model Design

Benchmark regression to build Equation (6).

$$GTFP_{i,t} = \pi_0 + \pi_1 FIN_{i,t} + \varepsilon_{i,t} \tag{6}$$

where π_0 denotes the constant term, $GTFP_{i,t}$ denotes the green total factor productivity, $FIN_{i,t}$ denotes the efficiency of financial resources allocation, and $\varepsilon_{i,t}$ denotes the random error term.

To test the spatial spillover effect of financial resource allocation efficiency on green total factor productivity, the analysis constructs a dynamic spatial Durbin model, as shown in Equation (7).

$$GTFP_{i,t} = \gamma * GTFP_{i,t-1} +* \rho W_{i,j} * GTFP_{j,t} + \beta_1 * FIN_{i,t} + \theta_1 W_{i,j} * FIN_{j,t} + \beta_2 X_{i,t} + \theta_2 W_{i,j} * X_{j,t} + u_i + v_t + \varepsilon_{i,t} \tag{7}$$

where $GTFP_{i,t-1}$ denotes the lagged term of green total factor productivity by one period, $X_{i,t}$ stands for control variables,$u_i$represents individual fixed effects, $v_t$denotes time fixed effects, and $\varepsilon_{i,t}$ signifies the random error term.

$W_{i,j}$ represents the spatial weight matrix, as defined in Equation (8). This matrix is constructed based on the Queen contiguity criterion, forming a 0-1 adjacency matrix where regions i and j are set to 1 if they are adjacent and 0 otherwise. Additionally, Hainan is considered adjacent to Guangdong.

$$W_{ij} = \begin{cases} 1, & \text{Spatial units i and j are neighboring} \\ 0, & \text{Spatial units i and j are not neighboring} \end{cases} \tag{8}$$

4. Empirical Analysis

4.1 Spatial Autocorrelation Test of Green Total Factor Productivity

Table 4 shows the global Moran's index for GTFP, and the Moran's I values are all positive, indicating a significant positive spatial correlation for GTFP.

Table 4: Global Moran's Index of GTFP

year	*Moran's I*	*P*	*Z*
2011	0.275	0.010***	2.568
2012	0.307	0.005***	2.837
2013	0.310	0.004***	2.846
2014	0.313	0.004***	2.861
2015	0.320	0.004***	2.909
2016	0.312	0.004***	2.863
2017	0.299	0.006***	2.741
2018	0.277	0.010***	2.575
2019	0.265	0.014**	2.470
2020	0.255	0.018**	2.372
2021	0.235	0.025**	2.241
2022	0.095	0.285	1.070
Note: ***,** or * denotes significance at the level of 1%,5%or10%,respectively.			

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Further insight into the spatial clustering characteristics of the observations can be gained from the Moran scatter plot. The distribution of observations in the first and third quadrants indicates a strong degree of spatial dependence, while observations in the second and fourth quadrants indicate a certain degree of spatial heterogeneity. The Moran scatter plot of GTFP is shown in Figure 1. Moran scatter plots are drawn for two years, 2011 and 2022. Most provinces are distributed in the first and third quadrants, and a few provinces are distributed in the second and fourth quadrants, indicating that the distribution of GTFP in each province shows spatial clustering characteristics, that there is a positive spatial correlation of GTFP, and that spatial econometric models should be taken into account in modelling.

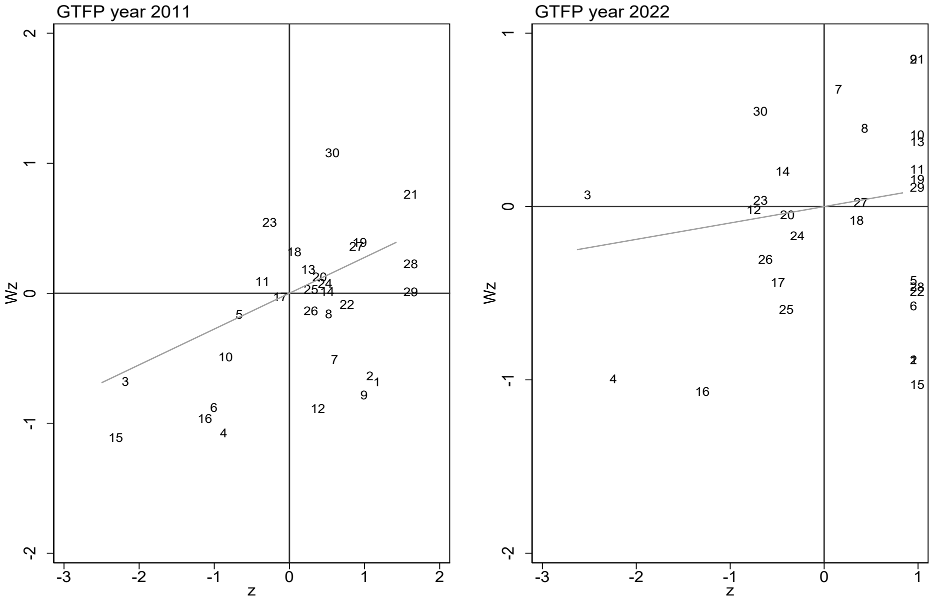

Figure 1: GTFP Moran Scatterplot for 2011, 2011

4.2 LM Test and Wald Test

Table 5 shows the results of the LM test and Wald test, which are both significant at the 5% confidence level, indicating that the Spatial Durbin Model does not degenerate into a Spatial Lag Model or a Spatial Error Model. The Hausman test was conducted with a chi-square value of 25.93 and a p-value of 0.039, which is less than 5%. Therefore, the null hypothesis of random effects was rejected, and the fixed effects model was used for analysis.

Table 5: The results of LM test and Wald test

Test	Statistic	p-value
Spatial error:		
Moran's I	18.942	0.000***
Lagrange multiplier	330.004	0.000***
Robust Lagrange multiplier	110.952	0.000***
Spatial lag:		
Lagrange multiplier	223.494	0.000***
Robust Lagrange multiplier	4.442	0.035**
Wald:		
SDM→SAR		0.003***
SDM→SEM		0.002***

Note: ***,** or * denotes significance at the level of 1%,5%or10%, respectively.

4.3 Benchmark Regression

Table 6 shows the results of the benchmark regression, and the value of the FIN coefficient is significantly positive, indicating that the efficiency of financial resource allocation can promote green total factor productivity.

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Table 6: Benchmark Regression Results

GTFP	Coefficient	St. Err.	t-value	p-value	[95% Conf.	Interval]
FIN	0.17	0.035	4.84	0.000***	0.098	0.241
Constant	0.79	0.029	27.58	0.000***	0.731	0.848
Mean dependent var		0.879	SD dependent var		0.093	
R-squared		0.193	Number of obs		360	
F-test		23.414	Prob > F		0.000	

Note: ***,** or * denotes significance at the level of 1%,5%or10%,respectively.

4.4 Spatial Spillover Effects

As shown in Table 7, the coefficient for L1. GTFP is significantly positive at the 1% level, indicating the presence of temporal lag in GTFP; high green total factor productivity in the previous period is likely to lead to an increase in the current period's GTFP. The coefficient for L1. WGTFP is also significantly positive at the 1% level, indicating significant spatial spillover effects in GTFP; an increase in local green total factor productivity positively impacts the green total factor productivity of surrounding regions. Both the main effect and spatial effect coefficients of financial resource allocation efficiency and the control variables are significantly positive at the 1% level. The influence of financial resource allocation efficiency (FIN) on green total factor productivity is significantly positive, exhibiting notable spatial spillover effects.

In the short term, both the direct effect coefficient and indirect effect coefficient of FIN are significantly positive, suggesting that FIN not only promotes local green total factor productivity but also enhances the green total factor productivity of neighboring regions. In the long term, only the direct effect coefficient remains significant, indicating that over a longer period, the financial resource allocation efficiency primarily promotes the local green total factor productivity.

Table 7: Results of Spatial Spillover Effects

GTFP	Coefficient	Std. err.	z	P>z	[95%con.	interval]
Main						
L1.*GTFP*	1.515	0.046	33.090	0.000***	1.425	1.604
L1.W*GTFP*	1.627	0.110	14.750	0.000***	1.411	1.843
FIN	0.074	0.008	8.980	0.000***	0.058	0.090
IS	-0.242	0.060	-4.060	0.000***	-0.358	-0.125
ECO	-0.312	0.031	-9.910	0.000***	-0.373	-0.250
LAB	-0.914	0.060	-15.340	0.000***	-1.031	-0.797
GOV	4.625	0.201	23.060	0.000***	4.232	5.018
OPEN	-0.281	0.030	-9.220	0.000***	-0.340	-0.221
URB	1.878	0.111	16.880	0.000***	1.660	2.096
Wx						
FIN	0.464	0.019	24.350	0.000***	0.426	0.501
IS	0.997	0.103	9.680	0.000***	0.795	1.199
ECO	-0.410	0.055	-7.510	0.000***	-0.517	-0.303
LAB	-1.394	0.126	-11.070	0.000***	-1.641	-1.147
GOV	15.859	0.333	47.660	0.000***	15.207	16.511
OPEN	-1.526	0.053	-28.860	0.000***	-1.629	-1.422
URB	10.391	0.262	39.610	0.000***	9.877	10.905
Spatial rho	0.145	0.075	1.930	0.053	-0.002	0.292
Variance sigma2_e	0.000	0.000	14.110	0.000***	0.000	0.000
FIN						
SR_Direct	0.093	0.012	8.070	0.000***	0.071	0.116
SR_Indirect	0.550	0.053	10.380	0.000***	0.446	0.653
SR_Total	0.643	0.062	10.410	0.000***	0.522	0.764
LR_Direct	-0.257	0.054	-4.780	0.000***	-0.363	-0.152
LR_Indirect	0.022	0.045	0.490	0.627	-0.067	0.111
LR_Total	-0.235	0.012	-19.400	0.000***	-0.259	-0.211

Note: ***,** or * denotes significance at the level of 1%,5%or10%,respectively.

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4.5 Robustness Test

To test the robustness of the above model and analysis results, the 0-1 matrix is first replaced with an inverse distance spatial weight matrix, as shown in Equation (9). Additionally, the years 2015 and 2020, which may contain outliers due to macroeconomic influences, are excluded from the analysis. The revised model analysis results are presented in Table 8. The coefficients of L1. GTFP and L1. WGTFP are significantly positive, and the coefficients of the main and spatial effects of the other variables do not differ greatly, and they all show varying degrees of significance. The model is robust.

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{cases} \tag{9}$$

Table 8: Results of Robustness Test

GTFP	Inverse Distance Matrix			Drop years 2015 and 2020		
	Coefficient	z	P>z	Coefficient	z	P>z
Main						
L1.*GTFP*	2.135	43.510	0.000***	2.360	39.510	0.000***
L1.W*GTFP*	14.596	34.260	0.000***	18.652	35.240	0.000***
FIN	0.037	4.140	0.000***	-0.052	-5.160	0.000***
IS	-1.189	-19.500	0.000***	-1.313	-19.000	0.000***
ECO	-0.858	-26.860	0.000***	-1.014	-27.670	0.000***
LAB	-0.884	-15.970	0.000***	-0.824	-13.050	0.000***
GOV	6.328	32.170	0.000***	5.526	24.370	0.000***
OPEN	0.002	0.060	0.956	0.046	1.310	0.189
URB	-0.505	-4.360	0.000***	-0.462	-3.480	0.000***
Wx						
FIN	1.622	25.450	0.000***	1.113	15.620	0.000***
IS	-0.100	-0.300	0.763	1.574	4.240	0.000***
ECO	2.206	12.190	0.000***	2.054	9.720	0.000***
LAB	-11.755	-27.770	0.000***	-11.428	-23.770	0.000***
GOV	109.136	105.720	0.000***	98.059	86.430	0.000***
OPEN	-5.888	-25.600	0.000***	-6.555	-24.400	0.000***
URB	51.901	66.260	0.000***	54.476	59.730	0.000***
Spatial rho	3.317	13.330	0.000***	2.734	9.610	0.000***
Variance sigma2_e	0.000	16.590	0.000***	0.000	15.100	0.000***
Note:***,** or * denotes significance at the level of 1%,5%or10%,respectively.						

5. Conclusions

This paper employs the dynamic spatial Durbin model to assess the relationship between financial resource allocation efficiency and green total factor productivity in 30 provinces and cities in China. The findings indicate that there is a time lag in green total factor productivity, and that financial resource allocation efficiency can promote green total factor productivity in local and neighbouring areas in the short term. However, in the long term, it will have a more significant role in promoting the local area.

The following recommendations are made accordingly: (1) The government and financial institutions should jointly formulate policies to improve the efficiency of financial resource allocation, such as reducing the handling fees for financial business, simplifying the loan approval process, and lowering the financing threshold for green enterprises.

(2) Promote financial innovation: Encouraging financial institutions to engage in green financial innovation is essential for promoting the deep integration of financial technology with green industries. This integration enhances the efficiency and precision of financial resource allocation. Developing green financial technology platforms further improves the inclusiveness and convenience of financial services.

(3) Strengthen financial regulation and financial services: Strengthening the regulatory oversight of financial institutions is crucial to mitigating financial risks and ensuring the rational allocation and effective utilization of financial resources. Additionally, enhancing the evaluation and monitoring of green financial projects is necessary to ensure the transparency and stability of fund flows into green industry sectors.

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(4) Encouraging financial institutions to increase credit provision to green enterprises and projects is essential for enhancing the flexibility and adaptability of financial resource allocation. Simultaneously, establishing specialized green finance teams to offer tailored financial services can help address the financing challenges faced by green enterprises.

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